

Research Article

Condition Assessment of Tower and Mast Structures Monitored within One Cluster under Changing Environments

Changping Li ^{1,2}, Xinteng Ma ¹, and Yang Liu ¹

¹School of Transportation Science and Engineering, Harbin Institute of Technology, Harbin 150001, China

²China Tower Corporation Limited Harbin Branch, Harbin 150090, China

Correspondence should be addressed to Yang Liu; ly7628@hit.edu.cn

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Numerous communications and power towers are distributed around urban districts. To ensure the safety of tower and mast structures, an effective measurement is to establish a simple structural health monitoring (SHM) system for each tower structure to obtain continuous deformation data of all structures. However, there is little research focusing on evaluating the condition of tower and mast structures monitored within one cluster using deformation monitoring data. To address this issue, a condition assessment approach combining principal component analysis (PCA) with cross-validation is proposed in this study. The PCA-based method is applied to mitigate the influence of environmental temperature and speed load on the horizontal displacement monitoring data, and novelty detection based on cross-validation is adopted to evaluate the condition of all the tower and mast structures monitored within one cluster. Finally, the effectiveness of the proposed method is demonstrated using monitoring data obtained from actual tower and mast structures.

1. Introduction

Structural health monitoring (SHM) technology has been developed rapidly for decades, and some important civil infrastructures have been equipped with SHM systems to detect structural damage and evaluate the safety of structures [1–4]. With the monitored data, many sensor measurements [5, 6] and condition assessment methods [7, 8] have been used to identify useful structural information to optimize maintenance schedules for structures in service.

Among the multiple methods, vibration-based condition evaluation approaches have received much attention because they are nondestructive to structures and vibration data are easy to obtain [9–13]. However, this type of method also has one significant drawback since the structures are generally operating under changing environments and the variation in the modal parameters of structures can be affected by environmental factors [14–19]. It is difficult to evaluate structural conditions directly with massive monitored data. In a previous study, Farrar et al. [20] found that the modal frequency change induced by environmental

temperature differences even exceeded the impact of structural damage after studying the long-term monitoring data of the Alamosa Canyon Bridge. During the sixteen-week period of data accumulation for the Dowling Hall Footbridge, Moser and Moaveni [15] observed that the identified natural frequencies varied by 8%, while the measured temperatures ranged from 14°C to 39°C. After further analysis, the strongly correlated nonlinear relationship between natural frequencies and environmental temperature was drawn up. Martins et al. [21] established a correlation model between the structural responses acquired from various measurements and analyzed the interference of wind speed and temperature on the identification of modal parameters. Based on the above studies, it is obvious that environmental differences have a significant impact on structural modal parameters, which may further affect the accuracy of damage identification.

To eliminate the environmental effects on the condition assessment of structures, various means have been taken under investigation, which can be broadly divided into two categories: supervised and unsupervised methods. The

former [22, 23] needs to establish the relationship model between damage characteristics and various environmental factors to reduce the effects of the changing environment; however, it is hard to obtain the relationship model accurately due to the coupling interaction of different factors. The latter [24, 25] requires building the probabilistic diagnostic model in the reference state and substituting the monitored data into the model to diagnose the damage. This method uses environmental factors as latent vectors and seeks damage features that are insensitive to the changing environment by projection. In this method, the environmental effects are weakened by indirect conversion; meanwhile, some efficient structural information may be deleted during the projection process. Thus, both methods, using data acquired from a single structure, have unsolvable shortcomings in dealing with environmental effects. Considering that structures monitored in one cluster are serving in a similar environment, a damage detection method using a cluster analysis algorithm [26] is investigated, and the effects of the environment during the same monitoring period are indirectly mitigated by cross-validation.

Urban communications and power towers, serving as important components of civil infrastructure, are operating in hostile environments continuously. In addition, towers are generally connected by bolts, and previous studies show that typical damage, such as loosening and breakage [27, 28], occurs frequently at bolt joints. Although tower structures have been reinforced with better construction technology and stronger materials, the risk of structural accidents cannot be avoided [29]. Several studies have focused on the structural health monitoring of tower-like structures [30–32]; however, the accuracy of damage detection is seriously interfered with by the complex operating environment, including temperature and wind load. The number of tower and mast structures located in one urban district is relatively large, and the structural form of each tower and mast structure is simple. Therefore, a feasible way is to establish one cluster of tower and mast structures in which all the structures within this cluster are monitored by setting up a simple SHM system for each structure, e.g., the horizontal displacement monitoring system. However, little previous research has focused on the condition assessment of tower and mast structures monitored within one cluster under changing environments. In this paper, an approach combining principal component analysis (PCA) with cross-validation is proposed to evaluate the structural condition of tower and mast structures monitored within one cluster, and this method is effective in reducing the adverse effects of environmental temperature and speed load on the horizontal displacement monitoring data of tower and mast structures.

2. Condition Assessment of Tower and Mast Structures Using the Combination of PCA with Cross-Validation

2.1. Generation of the Condition Diagnosis Index. All the tower and mast structures with the same structural form

located in one urban district are defined as one cluster in this study, and if we establish the SHM system of the tower tip horizontal displacement, we obtain the continuous displacement monitoring data of all the structures within one cluster. With this definition, all the tower and mast structures belonging to one cluster are operated under similar environmental action; thus, the displacement monitoring data of different tower structures are highly correlated. On this basis, a cluster-based condition assessment approach is proposed, in which the environmental impact on the displacement monitoring data is reduced by using the PCA-based method combined with the cross-validation strategy.

Assume that $\mathbf{y}_i \in \mathbb{R}^{v \times 1}$ is the tower tip displacement monitoring data vector at the i th sampling point, where v represents the number of measured points of any two tower and mast structures monitored within one cluster. Take the initial dataset as the healthy state of structures and assemble the first n monitoring data vector into a data matrix \mathbf{Y}_1 , which can be expressed as follows:

$$\mathbf{Y}_1 = [\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n]. \quad (1)$$

This part of the data can be used to build a data model under the health state of structures, whose covariance matrix is defined as follows:

$$\Sigma = \frac{1}{n} \sum_{i=1}^n (\mathbf{y}_i - \boldsymbol{\mu})(\mathbf{y}_i - \boldsymbol{\mu})^T, \quad (2)$$

where $\boldsymbol{\mu}$ is the mean vector of \mathbf{Y}_1 .

Taking the singular value decomposition (SVD), the covariance matrix Σ can be expressed in the following form:

$$\Sigma = [\mathbf{U}_1 \quad \mathbf{U}_2] \begin{bmatrix} \mathbf{S}_1 & 0 \\ 0 & \mathbf{S}_2 \end{bmatrix} \begin{bmatrix} \mathbf{U}_1^T \\ \mathbf{U}_2^T \end{bmatrix}, \quad (3)$$

where \mathbf{S}_1 and \mathbf{S}_2 are diagonal matrices constructed by different parts of singular values of the matrix Σ , respectively, and they are described as follows:

$$\begin{aligned} \mathbf{S}_1 &= \text{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_g^2), \\ \mathbf{S}_2 &= \text{diag}(\sigma_{g+1}^2, \sigma_{g+2}^2, \dots, \sigma_v^2), \end{aligned} \quad (4)$$

where σ_i^2 is the square of the i th singular value and arranged in descending order. During the SVD process, the i th principal component contains more sample information if the corresponding singular value σ_i is larger.

Since environmental factors have a significant impact on the monitoring data of structures, the first g principal components are often selected to represent the influence of environmental factors in practical applications. To take advantage of more effective information, the selection of g should refer to the cumulative contribution rate of principal components I , which can be defined as follows:

$$I = \frac{\sum_{i=1}^g \sigma_i^2}{\sum_{i=1}^v \sigma_i^2} > I_0, \quad (5)$$

where I_0 refers to the limit value of the cumulative contribution.

Based on the above analysis, the data model $\{\mu, \mathbf{U}_2, \mathbf{S}_2\}$ under the healthy state can be established by using the monitoring data, where \mathbf{U}_2 is the singular vector with respect to \mathbf{S}_2 . The next process is to extract the remaining data from the initial data set and assemble them into data matrix \mathbf{Y}_2 , as follows:

$$\mathbf{Y}_2 = [\mathbf{y}_{n+1}, \mathbf{y}_{n+2}, \dots, \mathbf{y}_{n+k}], \quad (6)$$

with the data model $\{\mu, \mathbf{U}_2, \mathbf{S}_2\}$ and data matrix \mathbf{Y}_2 , we can construct the condition diagnosis index by using the following steps. First, the modified data vector by the data model under the healthy state of structures can be obtained by the following equation:

$$\hat{\mathbf{y}}_j = \mathbf{y}_{n+j} - \boldsymbol{\mu}, \quad (j = 1, 2, \dots, k). \quad (7)$$

Then, a transition vector \mathbf{p}_j is calculated as follows:

$$\mathbf{p}_j = \mathbf{U}_2^T \hat{\mathbf{y}}_j. \quad (8)$$

Using the transition vector \mathbf{p}_j , the vector of the condition diagnosis index is established as follows:

$$\mathbf{r} = \{r_1, r_2, \dots, r_k\}, \quad (9)$$

where each element is defined as follows:

$$r_j = \mathbf{p}_j^T \mathbf{S}_2^{-1} \mathbf{p}_j. \quad (10)$$

The above process achieves the target of removing the environmental impacts on the displacement monitoring data of any two towers belonging to one cluster.

2.2. Condition Assessment between Any Two Tower and Mast Structures Monitored within One Cluster. The condition diagnosis index \mathbf{r} has basically excluded the influence of environmental factors, assume that \mathbf{r} obeys a Gaussian distribution for the healthy reference state, and the residual r_j satisfies the following probability distribution:

$$f(r_j|\theta) = e^{\{r_j b(\theta) + c(r_j) + d(\theta)\}}, \quad (11)$$

where $c(r_j)$ is the parameter of the probability distribution model and θ is a characteristic parameter.

For the Gaussian distribution, the parameter θ has mean value ν and variance σ^2 defined as follows:

$$\begin{aligned} b(\theta) &= \frac{\nu}{\sigma^2}, \\ d(\theta) &= -\frac{\nu}{2\sigma^2}. \end{aligned} \quad (12)$$

According to equation (11), the probability distribution model of \mathbf{r} can be written as follows:

$$f(\mathbf{r}|\theta) = e^{\{b(\theta) \sum_{j=1}^k r_j + \sum_{j=1}^k c(r_j) + d(\theta)\}}. \quad (13)$$

On this basis, the following hypothesis test is defined:

$$\begin{aligned} \mathbf{H}_0: \theta &= \theta_0, \\ \mathbf{H}_1: \theta &= \theta_1, \end{aligned} \quad (14)$$

where θ_0 represents that the tower and mast structures are healthy and θ_1 represents damage state. For the communications and power towers are connected mainly by bolts, the damage state includes the bolts loosening or corrosion which results in the overlarge horizontal displacement of the tower body.

For the state of tower and mast structures to be diagnosed, a hypothesis test is carried out to determine whether any two tower structures are in a normal operation state. First, the novelty detection factor under the healthy state is defined as follows:

$$\Lambda = \frac{f(\mathbf{r}|\theta_1)}{f(\mathbf{r}|\theta_0)} = e^{\{[b(\theta_1) - b(\theta_0)] \sum_{j=1}^k \zeta_{j+k} [d(\theta_1) - d(\theta_0)]\}}. \quad (15)$$

Taking the logarithm of equation (15), we can obtain the cumulative damage feature:

$$\Xi = \ln(\Lambda). \quad (16)$$

Considering the expression of Λ , the iteration relation of the condition diagnosis index Ξ is generated as follows:

$$\Xi_k = \Xi_{k-1} + (b(\theta_1) - b(\theta_0))(r_k + \rho), \quad (17)$$

where

$$\begin{aligned} \Xi_0 &= 0, \\ \rho &= \frac{d(\theta_1) - d(\theta_0)}{b(\theta_1) - b(\theta_0)}. \end{aligned} \quad (18)$$

When the value of Ξ_j is less than 0, let it be 0, and then the following condition diagnosis index under the healthy state is obtained:

$$\mathbf{\Gamma}^h = \{\Xi_1^h, \Xi_2^h, \dots, \Xi_j^h, \dots, \Xi_k^h\}, \quad (19)$$

where h represents the healthy state.

The condition diagnosis index is obtained by data statistics analysis, by which error probability is imported inevitably. Taking into account the 5% error probability of the condition diagnosis index, the threshold Q can be defined by the following equation:

$$Q = 0.95 \max\{\Xi_1^h, \Xi_2^h, \dots, \Xi_k^h\}. \quad (20)$$

Using the above method, the condition diagnosis index of tower structures under the state to be diagnosed is established as follows:

$$\mathbf{\Gamma}^d = \{\Xi_1^d, \Xi_2^d, \dots, \Xi_c^d, \dots, \Xi_{k_0}^d\}, \quad (21)$$

where d represents the state to be diagnosed and k_0 is the number of data samples to be diagnosed.

The condition diagnosis index under the state to be diagnosed should be compared with the threshold value.

When the value of the condition diagnosis index under the state to be diagnosed is larger than the threshold value Q , it is considered that one of any two towers A and B have potential structural damage; at this time, the value of the detection result $Z_{a,b}$ is denoted as 0. In contrast, the two towers are both considered to be healthy, and the value of the detection result $Z_{a,b}$ is denoted as 1.

$$\begin{cases} z_{a,b} = 0, & \Xi_c^d > Q, \\ z_{a,b} = 1, & \Xi_c^d < Q. \end{cases} \quad (22)$$

2.3. Decision of Condition Assessment of All the Tower and Mast Structures Monitored within One Cluster. The algorithm proposed in the previous section uses the monitoring data of any two tower structures belonging to one cluster. To avoid accidental misjudgment, a cross-validation strategy is applied to integrate the monitoring data obtained from all tower and mast structures monitored within one cluster and to evaluate the condition of all structures.

Assuming that m tower and mast structures are monitored within one cluster, the o th structure is used as the reference structure, and the results of condition assessment between any other structure and the reference structure are obtained using the method described in the previous section, recorded as \mathbf{z}_o . The reference structure is cyclically exchanged until all the other structures have been selected as the reference structure once. Then, the set of m verification results is denoted as matrix $\mathbf{z} \in \mathbb{R}^{m \times (m-1)}$, which can be expressed as follows:

$$\mathbf{z} = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_o, \dots, \mathbf{z}_m]^T = \begin{bmatrix} z_{2,1} & z_{3,1} & \cdots & z_{a,1} & \cdots & z_{m,1} \\ z_{1,2} & z_{3,2} & \cdots & z_{a,2} & \cdots & z_{m,2} \\ \vdots & \vdots & \ddots & \vdots & & \vdots \\ z_{1,o} & z_{2,o} & \cdots & z_{a,o} & \cdots & z_{m,o} \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ z_{1,m} & z_{2,m} & \cdots & z_{a,m} & \cdots & z_{m-1,m} \end{bmatrix}, \quad (23)$$

where $z_{a,o}$ is the result of the a th tower structure by taking the o th reference structure. According to the cross-validation strategy, total $m-1$ results can be obtained. The mean value of the abovementioned $m-1$ results is taken as the decision value of the condition assessment for the a th structure, which is defined as follows:

$$\gamma_a = \frac{1}{m-1} \sum_{o=1}^m z_{a,o} \quad (o \neq a), \quad (24)$$

where γ_a is the decision value of the condition assessment for the a th structure. If γ_a is more than 0, it indicates that the a th structure is healthy; if γ_a is equal to 0, it indicates that the a th tower structure is damaged.

3. Example of Actual Tower and Mast Structures Monitored within One Cluster

3.1. Description of the SHM System of Actual Tower and Mast Structures Monitored within One Cluster. Four communications tower and mast structures are monitored within one cluster located in one city district in Harbin, China. As shown in Figure 1, all the towers are built of steel material and approximately 40 m tall, with communication equipment installed on the top and supporting bracings held at the bottom part of the structure. Each structure is fixed to the ground by 16 high-strength bolts, as shown in Figure 2. The high-rise tower and mast structures operate under the wind load in urban areas, resulting in the complexity of vibration behavior. To obtain the changing regulation of horizontal displacement of four tower and mast structures, the tower tip horizontal displacement is monitored by using inclinometers (SCL3300-D01 3-axis inclinometers), and all the data are acquired and sent to the wireless network, as shown in Figure 3. The general specifications for the SCL3300-D01 component are presented in Table 1.

For each structure, one SHM system generally includes four parts: (1) sensing module, (2) data acquisition and transmission module, (3) data storage module, and (4) software module. As displayed in Figure 4, the 3-axis inclinometer is installed at the top of the tower, and all the tilt observation data of the four towers are collected simultaneously to form a cluster. All the collected data are transferred and stored in the local server, and the software can display and analyze data. With these four SHM systems, all four tower and mast structures are monitored within one cluster.

3.2. Demonstration of the Effectiveness of the Proposed Method. To verify the validity and dependability of the proposed condition assessment approach, all the horizontal displacement monitoring data of four tower and mast structures are adopted in this section. Additionally, the bolt loosening condition of structure A is carried out to simulate the damage case, as shown in Figure 5, considering that bottom bolt failure is the most common condition in practice.

For each structure, every sensor can simultaneously collect the horizontal displacement along the north-south (NS) direction and the east-west (EW) direction. The data acquisition frequency is 10 minutes. A total of 4000 sets of data samples under the healthy state are obtained, in which the first 2000 sets of data samples are used to generate Y_1 , and the last 2000 sets of data samples are used to obtain Y_2 . For the damaged condition, a total of 1000 sets of data samples are obtained. Using the tower height, the actual monitoring data of tower A and tower B can be transferred into displacements of the tower top, as shown in Figure 6.

To reflect the sensitivity of the proposed method to the damage that occurs in the structure, the proposed method is compared with the traditional novelty detection method

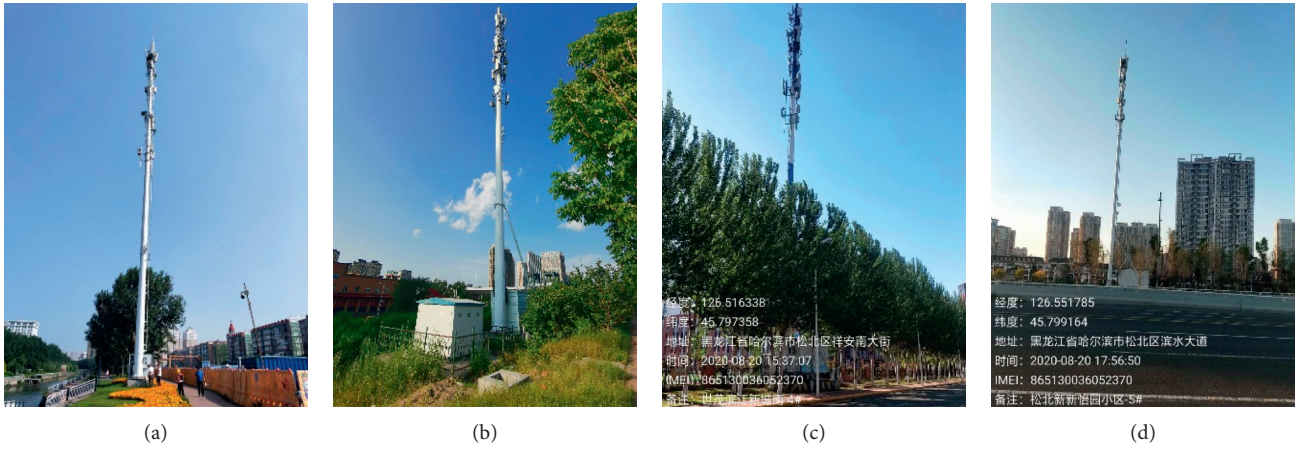


FIGURE 1: Photographs of four towers monitored within one cluster.

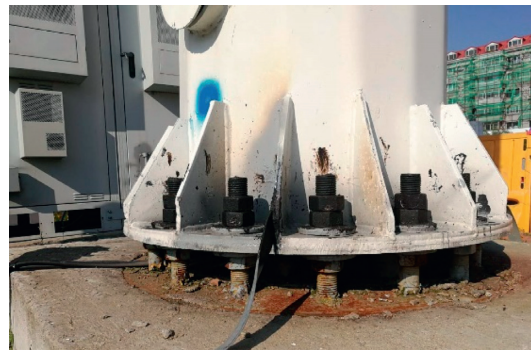


FIGURE 2: Photograph of the high-strength bolts of the junction.



FIGURE 3: Photograph of the inclinometers and data acquisition and transmission devices.

TABLE 1: General specifications of the SCL3300-D01 3-axis inclinometer.

Temperature range (°C)	Measurement range (°)	Offset error (°)	Offset temperature drift (°)
-40~125	-90~90	-1.15~1.15	-0.57~0.57

based on the Mahalanobis distance. The results of the proposed method for the two towers are shown in Figure 7, and the novelty detection results of the conventional method

for tower A are shown in Figure 8. The results show that the proposed method can effectively eliminate the influence of environmental factors and has a higher sensitivity to



FIGURE 4: The installation of the SHM system.

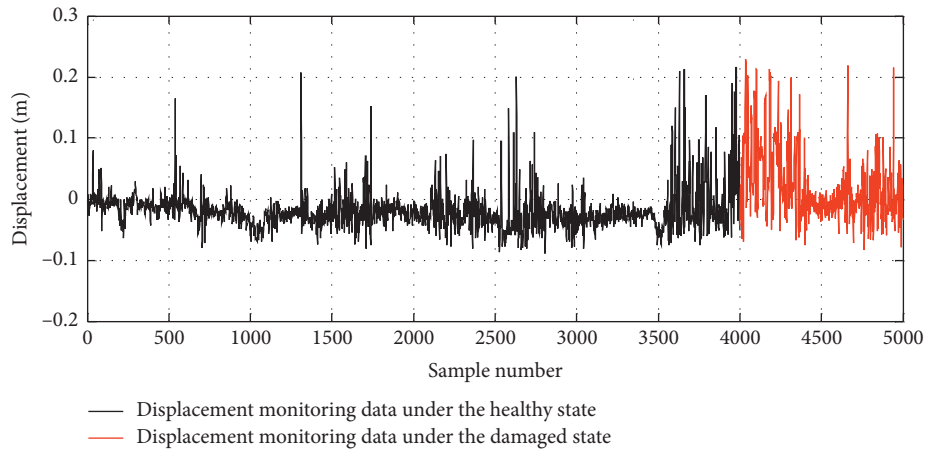


FIGURE 5: Photograph of bolt loosening of the junction of structure A.

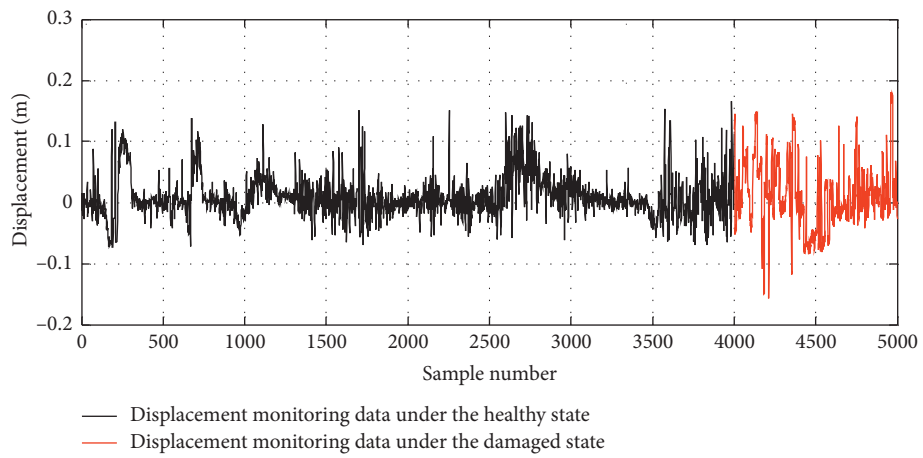
damage; thus, the proposed method successfully identifies the structural risk of bolt loosening.

Based on the cross-validation strategy, structure A in the cluster is selected as the reference tower. The proposed algorithm can effectively diagnose the damage of the reference tower and any other structure. On this basis, the reference tower is cyclically exchanged until all the other tower and mast structures are selected as the

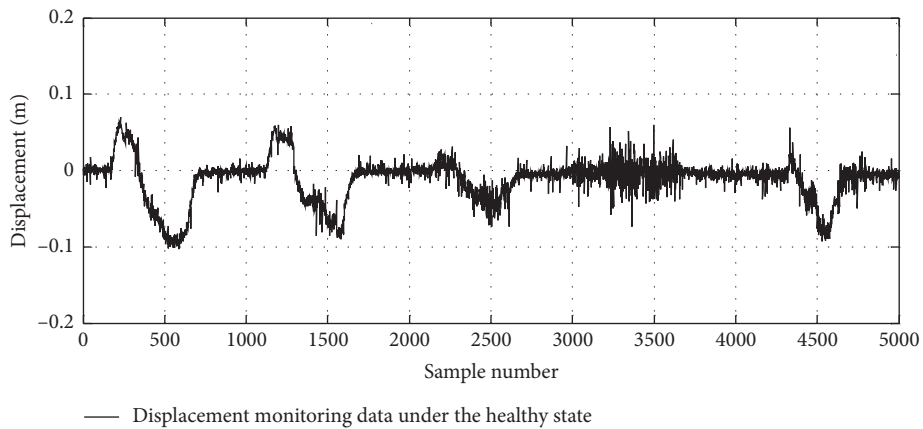
reference tower once. For the damage case, the cross-validation results of four structures are shown in Figure 9. The decision value of the condition assessment results is described as follows: $\gamma_A = 0$, $\gamma_B > 0$, $\gamma_C > 0$, and $\gamma_D > 0$. The results show that structure A is damaged. By using the cross-validation strategy, the monitoring data of all structures monitored within one cluster are integrated to avoid misjudgment.



(a)



(b)



(c)

FIGURE 6: Continued.

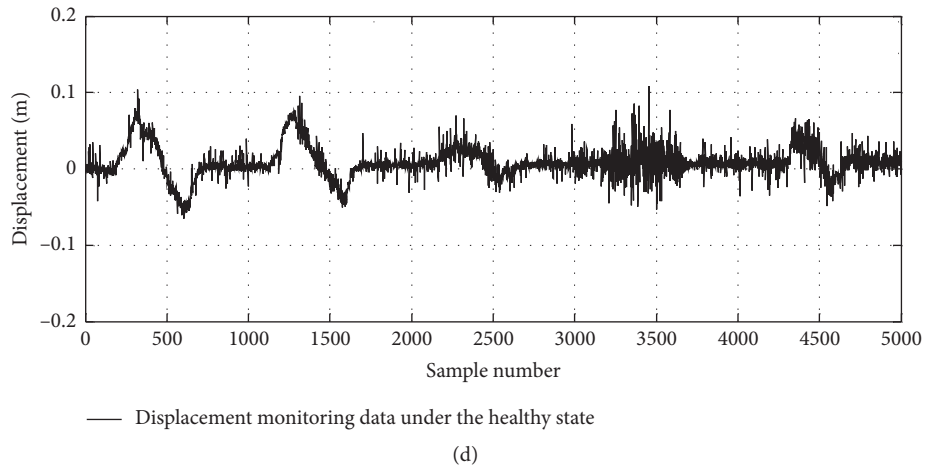


FIGURE 6: Displacement monitoring data of towers A and B. (a) The NS deformation of tower A. (b) The EW deformation of tower A. (c) The NS deformation of tower B. (d) The EW deformation of tower B.

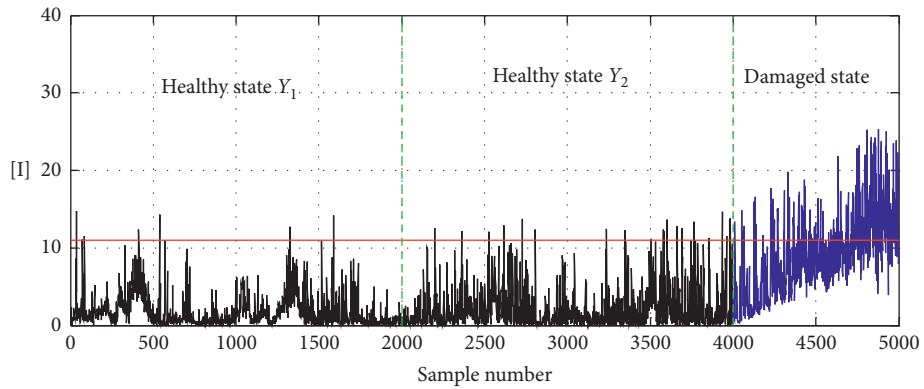


FIGURE 7: Condition assessment results of the proposed method.

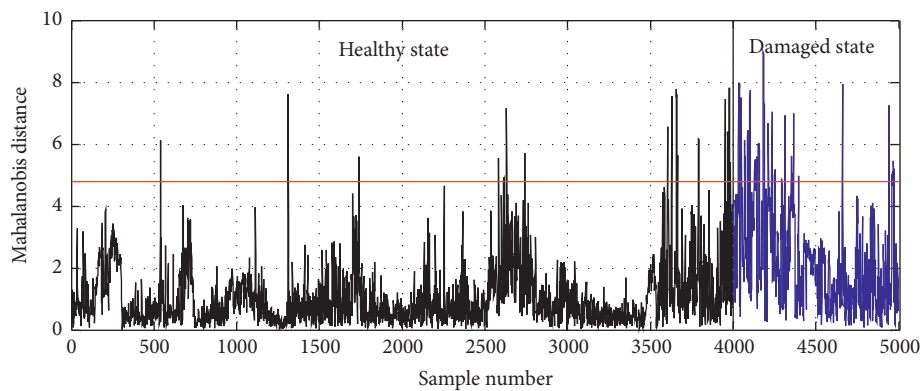


FIGURE 8: Results of the conventional method.

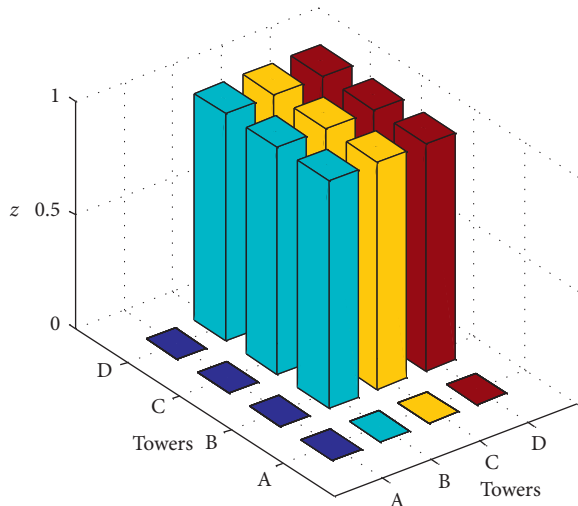


FIGURE 9: Assessment results of all tower and mast structures based on cross-validation.

4. Conclusions

In this paper, a method is proposed for evaluating the condition of all the tower and mast structures monitored within one cluster. The following conclusions are drawn:

- (i) The PCA-based method combined with cross-validation is an effective way to evaluate the condition of all tower and mast structures monitored within one cluster, and the influence of environmental factors on the deformation monitoring data of structures is effectively mitigated
- (ii) Examples show that, compared with the novelty detection method based on the Mahalanobis distance, the proposed method is effective in diagnosing the damaged condition of a structure under changing environments
- (iii) For practical situations, the tower tip angle can be used to monitor the long-term changing regulation of the horizontal displacement of tower and mast structures
- (iv) For practical applications, data acquisition and data transmission using the wireless network are promising for establishing the SHM systems of all tower and mast structures monitored within one cluster

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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